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Inducing risk preferences in multi-stage multi-agent laboratory experiments

Applied Economics

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Running Title: 'Inducing Risk Preferences in Multi-Stage Multi-Agent Experiments'

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Though there has been some debate over the practical efficacy of using binary lotteries for controlling risk preferences in experimental environments, the question of its theoretical validity within the contexts it is often used, namely multi-stage multi-agent settings, has not been addressed. Whilst the original proof of its validity featured a single-agent single-stage context, its practical use has seen a wide range of implementations. Practitioners have implicitly assumed that whenever the setting and form of implementation of RPIP they have chosen deviates from the original single-agent single-period proof, it remains theoretically valid. There has been virtually no debate in the practitioner literature on the theoretical validity of binary lotteries in a more general context, or on whether the form of implementation matters. The current article addresses these questions, establishes limitations on validity, and suggests some design principles for future implementation of binary lotteries for the purpose of controlling risk preferences.

Keywords: Experiments, Risk Preferences, Choice, Lotteries.
JEL Classification: C91; D81; D83

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I. Introduction

Many laboratory hypotheses concern the behaviour of individuals, either working alone, or in teams, or in competition, under conditions of risk.[1] The risk preferences of subjects participating in experiments designed to test such hypotheses are often not of primary interest to the researcher and are regarded as nuisance variables. To eliminate their effect, the development of appropriate metrics for testing theoretical predictions requires either measurement or control of risk preferences. A widely-used procedure for controlling risk preferences is to use binary lotteries to induce in all subjects risk preferences pre-specified by the experimenter; a procedure dubbed here the 'Risk-Preference Inducing Procedure' or 'RPIP'. The validity of RPIP was formally established in a seminal paper by Berg *et al.* (1986), following Roth and Malouf (1979), but only for the special case of a single experimental subject performing a single task. Unfortunately, this special case is not typically used by experimenters. In practice, subjects are usually required to perform a series of tasks, both to economize on experimental overheads and also because subject behaviour does not usually converge without some task repetition. Furthermore, experiments involving teams and agencies involve interaction between subjects. There has been virtually no debate in the practitioner literature on the theoretical validity of binary lotteries in these more general settings, or on whether the form of implementation matters. Practitioners have implicitly assumed that whenever the setting and form of implementation of RPIP they have chosen deviates from the original single-agent single-stage proof, it remains theoretically valid. In this paper, we show that this is not in general true. Restrictions on the structure and form of implementation are needed to ensure that RPIP is actually theoretically valid. In a recent theoretical contribution, Dobbs and Miller (2012) presented necessary and sufficient conditions for the validity of RPIP for non-interacting subjects performing a series of tasks. However,

[1] See Roth and Malouf (1979), Roth and Murnighan (1982), Cox *et al.* (1985, 1988), Berg *et al.* (1986, 1992, 2003), Murnighan *et al*. (1988), Roth *et al.* (1988), Waller (1988), Baiman and Lewis (1989), Cooper *et al.* (1989, 1990, 1992, 1993), Harrison (1989), Walker *et al.* (1990), Harrison and McCabe (1992), Prasnikar (1993), Rietz (1993), Cox and Oaxaca (1995), Blume *et al*. (1998), Selten *et al.* (1999), Sprinkle (2000), Fisher *et al.* (2002), Fisher *et al.* (2003), Frederickson and Waller (2005), Dobbs and Miller (2006, 2008, 2009), Harrison *et al.* (2013).

that analysis did not address the important class of experiments which feature multiple interacting subjects.

Empirical evidence from laboratory experiments on the effectiveness of RPIP for controlling risk preferences has been mixed, leading many researchers to abandon the technique altogether. Briefly, Berg *et al.* (1986), Walker *et al*. (1990) and Rietz (1993) found in favour of its effectiveness, and Cox *et al*. (1985) and Selten *et al*. (1999) found against.[2] Harrison *et al*. (2013) have recently argued that previous experiments on the effectiveness of RPIP for inducing risk neutrality have been confounded by failure of one or more auxiliary assumptions: a) subjects are not risk neutral over money payoffs; b) subjects use Nash strategies in experiments involving strategic games; and c) the reduction of compound probabilities axiom of Von Neumann Morgenstern Expected Utility Theory (EUT) holds. Their tests are the only ones that avoid making these 'confounding assumptions', and they find empirical support for the effectiveness of RPIP when subjects perform single or multiple tasks, without strategic interaction with other subjects. Harrison *et al*. (2013, p 150, fn 15)) also note, following Berg *et al*. (2008), that when the experimenter wishes to induce risk attitudes other than risk neutrality, the effective use of RPIP 'requires a model of decision making under risk that assumes linearity in probabilities'. As we shall see in the present paper, however, theoretical analysis demonstrates that neither linearity in probabilities nor Nash behaviour by subjects are necessary assumptions for the validity of RPIP, and therefore their falsification does not necessarily confound experiments involving RPIP. The analysis presented here thus permits a fresh appraisal of the empirical evidence employing RPIP.[3]

The fundamental contribution of the present article is to provide a general analysis of RPIP for all experiments, including those involving interaction between multiple agents performing a series of

[2] See Berg *et al*. (2008) for a review of this evidence.
3 For example, Selten *et al*. (1999, p 212) state 'If one wants to examine the question whether payoffs in binary lottery tickets induce risk neutral behavior, it is necessary to avoid a confounding effect which may be introduced by strategic interaction'. They cite Cooper *et al*. (1990, 1993), *inter alia*, as examples of this potential confounding effect. We show in the present paper that there is no confounding effect from using RPIP with strategic interaction in the papers by Cooper *et al*. (1990, 1993).

tasks. Claims to complete generality found in Berg *et al.* (1986, p. 281) and Berg *et al.* (2003, p. 145; 2008) have rested on an independence condition stated to be sufficient but not formally proved in this more general setting. Moreover, no necessary condition was proposed. Hence, the validity of RPIP for experiments that fail the sufficient condition is unclear, and no design fix has been articulated when RPIP is invalid. The present article proves a necessary and sufficient condition for the validity of RPIP for the most common form of implementation of the technique, and also shows that when the necessary condition fails, the validity of RPIP can be salvaged by a simple modification to the way in which it is implemented.[4] This modification has appeared in the experimental literature, though its use appears to be unrelated to the purpose of achieving valid implementation of RPIP, while some experimental research designs have failed to use appropriate modifications and have therefore misapplied RPIP. We find therefore that RPIP can be robust to the number and interaction of subjects in an experiment, depending on its practical implementation. The most important implications of our results are for the experimental literature testing propositions from the economics of organisational architecture. Many experiments in this literature test theoretical predictions in contexts involving multiple decision tasks and multiple agents, where the predictions are typically sensitive to the risk preferences of individual agents.[5]

The rest of the paper is divided into three sections. Section II introduces the notion of inducing risk preferences using RPIP, provides a formal demonstration that the validity of RPIP does not necessarily depend on subject preferences being linear in probabilities, and discusses the use of expected utility theory in the experimental literature. Section III presents the notation and framework adopted for general analysis of RPIP, reviews the literature on the context and implementation of RPIP, and states two propositions relating to the use of RPIP in laboratory experiments. Proofs of these propositions are contained in an appendix. Section IV offers conclusions and implications for the design of experiments.

[4] This generalizes the results in Dobbs and Miller (2012) to include *all* laboratory experiments, including those involving subject interaction as well as multiple tasks.
[5] See Laffont and Martimort (2002).

II. RPIP for a Single Subject Performing a Single Task

In order to introduce the notion of inducing risk preferences using the RPIP method, it is useful to review the single-subject single-task problem analysed in Berg *et al.* (1986). Consider a single subject performing a single task in a laboratory experiment that involves an uncertain monetary reward to the subject.[6] Specifically, the subject must choose an action a from a set of actions, $a \in A$. In return for action a, the subject receives a random payment x from a finite set of possible rewards, $x \in X$, with conditional density $g(x|a)$. Berg *et al.* assume the subject's preferences can be represented by a von Neumann-Morgenstern (*VNM*) utility function $U(x)$, so the decision problem can be summarized as:

$$\max_{a \in A} \int_{x \in X} g(x|a)U(x)dx \tag{1}$$

where X and $g(x|a)$ are specified in the experimental design. However, since $U(x)$ is not known by the experimenter, the behaviour of the subject, his chosen a, is likewise unpredictable by the experimenter.

If instead of the above experimental design, RPIP is applied, then the subject is rewarded in an 'experimental currency', exchanged later for probability points assigned in respect of a two-prize lottery. Suitable choice of the rate at which the experimental currency is exchanged for probability points can, in theory, allow the experimenter to 'induce' in the subject any desired risk preferences over lotteries involving the experimental currency. Denote the random reward of 'experimental currency' by $q \in Q$, with conditional density $f(q|a)$, where Q is a closed bounded interval of the set of real numbers. Choose for the binary lottery two money prizes, $\overline{x}, \underline{x}$, with $\overline{x} > \underline{x}$, so that $U(\overline{x}) >$

[6] It will be convenient to assume the reward is a money payment to the subject, but in general rewards need not be monetary. For example, in Isaac *et al.* (1994), rewards were given in points of course credit.

$U(\underline{x})$, and define a function $G(q) \equiv P(\overline{x}|q) = 1 - P(\underline{x}|q)$ for exchanging q into probability points for the binary lottery.[7] Then the subject's decision problem becomes

$$\max_{a \in A} \int_{q \in Q} f(q|a)\{P(\overline{x}|q)U(\overline{x}) + (1 - P(\overline{x}|q))U(\underline{x})\}dq \tag{2}$$

$$= \max_{a \in A} \int_{q \in Q} f(q|a)\{G(q)U(\overline{x}) + (1 - G(q))U(\underline{x})\}dq \tag{3}$$

$$= \max_{a \in A} \left(\int_{q \in Q} f(q|a)G(q)[U(\overline{x}) - U(\underline{x})]dq + \int_{q \in Q} f(q|a)U(\underline{x})dq \right) \tag{4}$$

$$= \max_{a \in A} \left([U(\overline{x}) - U(\underline{x})] \int_{q \in Q} f(q|a)G(q)dq + U(\underline{x}) \int_{q \in Q} f(q|a)dq \right) \tag{5}$$

Since $\int_{q \in Q} f(q|a)dq = 1$, Equation 5 reduces to

$$\max_{a \in A} \left(U(\underline{x}) + [U(\overline{x}) - U(\underline{x})] \int_{q \in Q} f(q|a)G(q)dq \right) \tag{6}$$

Finally, since $U(\overline{x}) > U(\underline{x})$ in Equation 6, the optimal solution, a^*, can be written as

$$a^* = \underset{a \in A}{\operatorname{argmax}} \left(\int_{q \in Q} f(q|a)G(q)dq \right) \tag{7}$$

This shows that the subject should in theory behave as if maximising the expected value of the exchange function $G(q)$, a function chosen by the experimenter. By choosing a convex, linear or

[7] For ease of comparison, where possible the notation is that used in Berg *et al.* (1986). The one exception is the notation for the two money prizes which, in Berg *et al.* (1986), were (x_1, x_2). In our later generalisation, subscripts are reserved for distinguishing between multiple stages.

concave increasing function $G(q)$, the experimenter can then induce in the subject, respectively, risk-seeking, risk-neutral or risk-averse preferences over q.

Although the above analysis has been framed in terms of Von Neumann Morgenstern Expected Utility Theory (EUT), RPIP can be shown to be consistent with other theories of preference ordering, including rank-dependent cumulative prospect theory. The following proof of this fact relates to the single-task single-subject case analysed in Berg *et al*. (1986). It demonstrates that, contrary to what many contributors have claimed, the effectiveness of the RPIP procedure is *not* dependent on an assumption of EUT with linear probabilities.[8]

Write the subject's value function, indexing his preferences, as $V(p(a), \overline{x}, \underline{x})$, where $\overline{x}$ is the preferred prize, and $p(a)$ is the probability of receiving it, as a function of the subject's decision. As noted, but not proved, in Selten *et al*. (1999) and in Harrison *et al*. (2013), for the context of inducing risk-neutrality, a sufficient assumption for RPIP to work as intended is that the value function is strictly increasing in the probability of winning the preferred prize $p(a)$.

To see this, suppose a^* is a unique global maximum. Then $V(p(a^*), \overline{x}, \underline{x}) > V(p(a'), \overline{x}, \underline{x})$, for all $a' \neq a^*$. But $V(p(a), \overline{x}, \underline{x})$ is strictly increasing in $p(a)$. Hence $p(a^*) > p(a')$ for all $a' \neq a^*$, and a^* hence is also the global maximum for the function $p(a)$: that is, a subject behaves as if maximising the probability of winning the preferred prize, $p(a)$.[9] Now, by definition of RPIP, $p(a) = \int_{q \in Q} f(q|a)G(q)dq$, where $G(q)$ is the conditional probability of winning the preferred prize. It follows immediately from this definition that a subject who behaves as if maximising $p(a)$ also behaves as if maximising the expected value of the function $G(q)$. In the experimental design, this function can be made linear with regard to q for risk neutral behaviour, strictly concave for risk aversion, or strictly convex for risk-seeking. Thus the sufficient condition, that the subject's index of

[8] Our thanks to an anonymous referee for raising this question.

[9] If this were not true, there would exist an action a' such that $p(a') \geq p(a^*)$, but then $V(p(a'), \overline{x}, \underline{x}) \geq V(p(a^*), \overline{x}, \underline{x})$ because $V(p(a), \overline{x}, \underline{x})$ is strictly increasing in $p(a)$, which contradicts the assumption that there is a unique global maximum at a^*.

preferences is strictly increasing in $p(a)$, is valid for inducing *any* type of risk preferences, not only the risk-neutrality referred to by Selten *et al*. (1999) and Harrison *et al*. (2013).

The above proof relies on strict monotonicity, which is satisfied by rank-dependent cumulative prospect theory.[10] Hence we have provided a value function that is nonlinear in probability, yet consistent with induced preferences for risk neutrality, risk aversion or risk-seeking. This shows that preferences being linear in probability is not a necessary condition for inducing any form of risk preferences over *q*, and that therefore preferences being nonlinear in probability does not necessarily confound experiments involving RPIP.

From this point on, we confine ourselves to analysis of RPIP within the EUT framework. Although, as shown above, RPIP may be used in conjunction with other theories of preferences, almost all researchers using RPIP have chosen to develop null hypotheses within the EUT framework, even when their motivation is to test for violations of EUT.[11] A good example is Frederickson and Waller (2005), where the motivation came from prospect theory in order to explain why, in an agency context, bonus and penalty frames in economically equivalent salary schemes affected preferences and choices. The null hypothesis was formulated using EUT and RPIP, and the test looked for significant departures from this benchmark. As stated in Roth *et al*. (1988, p 808):

> *We do not need to suppose in our interpretation of these experiments that the use of binary lottery games has controlled for the behavior of the experimental subjects, who may or may not be utility maximisers. Rather, the purpose of using binary lottery games is to control the predictions of the theory, specifically Nash's model of bargaining. The question of whether the various predictions of a theory like Nash's are good descriptions of behavior is independent of whether utility theory is a good description of individual choice. (That is, some of the predictions could be correct even if individuals aren't utility maximisers, and vice versa.) But since Nash's model is stated in terms of the expected utility available to the bargainers, it is necessary to control for what the utility of utility maximisers would be, to know what the predictions of the theory in any particular situation are.*

[10] See Gonzalez and Wu (1999), who also provide laboratory evidence relating rank-dependent cumulative prospect theory to choice problems involving binary lotteries. Also implicit in the above argument is the reduction of compound probabilities assumption, at least for binary lotteries.

[11] Examples include Roth and Malouf (1979), Roth and Murnighan (1982), Cox *et al.* (1985), Berg *et al.* (1986, 1992), Murnighan *et al*. (1988), Roth *et al*. (1988), Waller (1988), Baiman and Lewis (1989), Cooper *et al.* (1989, 1990, 1992, 1993), Harrison (1989), Walker *et al.* (1990), Blume *et al*. (1998), Sprinkle (2000), Frederickson and Waller (2005), and Dobbs and Miller (2006).

We now turn to consideration of how risk preferences can be controlled in a more general setting than was considered in Berg *et al*. (1986). In particular, we allow for multiple subjects and multiple decision stages, either interdependent or independent, and provide guidance on the experimental research design needed for effective control using the binary lottery procedure.

III. RPIP for Sequential Multi-Stage Environments

As remarked in the introduction, although RPIP was originally proven only for the case of a single agent dealing with a single (risky) decision, in practice, applications often involve multiple interacting agents and/or multiple decision stages. In this section, a characterisation of the multi-stage experimental environment for a finite number of interacting subjects is developed. Alternative 'bundling' methods by which RPIP might be implemented in such settings are described and cross-referenced to the experimental literature, along with a discussion of what exactly the objective of the risk-preference-inducing procedure might be in such a multi-stage context. The section provides two propositions that are likely to prove helpful when designing experiments. The first gives a necessary and sufficient condition involving the experimental design for the standard implementation of RPIP to be effective. This condition will not be satisfied for some experimental designs, but the second proposition shows that a failsafe albeit not widely used implementation of RPIP is valid for all types of multiple-subject multi-stage experimental environments. Thus, for experimental designs that fail the necessary condition in Proposition 1, the alternative design in Proposition 2 can be used instead.

Sequential multi-stage multiple-subject experiments

A more general analysis of RPIP requires a mathematical characterisation of multiple-subject multi-stage experiments. Within this setting, we focus on the problem of inducing risk-preferences in an arbitrary subject. There are T stages in the experiment and n subjects interacting at every stage. The choice of a typical subject, who we will call subject i, at stage t of the experiment is denoted $a_{it} \in$

$A_{it}, (t = 1, \dots, T)$ and the set of choices of all other subjects except subject i is denoted $a_{-it} \in A_{-t}, (t = 1, \dots, T)$. In order to control risk preferences at each stage, subject i is given a separate award of experimental currency $q_{it} \in Q_{it}, (t = 1, \dots, T)$ for each stage. All of these features are assumed given in an experimental design that incorporates use of RPIP. Let $a_i = \{a_{i1}, \dots, a_{iT}\}$, $A_i = A_{i1} \times \dots \times A_{iT}$, $a_{-i} = \{a_{-i1}, \dots, a_{-iT}\}$, and $q_i = \{q_{i1}, \dots, q_{iT}\}$, with generalized conditional density function[12]

$$
\begin{aligned}
f(q_i | a_i, a_{-i}) = f_{i1}(q_{i1} | a_{i1}, a_{-i1}) \times f_{i2}(q_{i2} | a_{i2}, a_{-i2}, a_{i1}, a_{-i1}, q_{i1}) \times \dots \\
\dots f_{iT}\left(q_{iT} | a_{iT}, a_{-iT}, a_{i(T-1)}, a_{-i(T-1)}, q_{i(T-1)}, \dots, a_{i1}, a_{-i1}, q_{i1}\right)
\end{aligned} \tag{8}
$$

Equation 8 allows for the possibility of interdependence between stages and subjects in an experimental design, whilst recognising the sequential nature of the stages. Thus the conditional density for q_{i1} may *only* depend on a_{i1} and a_{-i1}, but the conditional density for subsequent awards such as q_{i2} and q_{i3} may depend on both previous subject decisions and previous awards.

RPIP implementations with and without bundling

The most common method of implementing RPIP is to run a separate lottery for each award of experimental currency $q_{it}, t = 1, \dots, T$, with exchange functions, $G_{it}(q_{it}), t = 1, \dots, T$. In that case, the set of rewards, $q_i = \{q_{i1}, \dots, q_{iT}\}$, can be said to be partitioned into T distinct subsets. However, RPIP can be, and has been, implemented differently, with $S < T$ lotteries and $q_i = \{q_{i1}, \dots, q_{iT}\}$ accordingly partitioned into S distinct subsets. For example, in their study of the empirical performance of RPIP for inducing risk-neutrality, Selten *et al.* (1999) partitioned the set $q_i = \{q_{i1}, \dots, q_{i50}\}$ into $S = 25$ subsets of consecutive pairs of consequences:

$$G_{ik}(q_{i(2k-1)}, q_{i2k}) = q_{i(2k-1)} + q_{i2k}, \quad k = 1, \dots, 25 \tag{9}$$

[12] For any given value of q_{it}, the generalized conditional density function is either a probability frequency function or a probability density function. Analysis of expected values can then handle discrete, continuous or mixed distributions using the general Lebesgue-Stieltjes integral; see Billingsley (1995, p 228).

and in Frederickson and Waller (2005), a single lottery, $G_i(q_i)$, was employed for a total of forty stages involving pairs of subjects engaged in principal-agent games. In this latter paper, to induce risk neutrality for the principals, RPIP was implemented by setting:

$$G_i(q_i) = \frac{1}{40}\sum_{t=1}^{40} 3.0534 q_{it} \tag{10}$$

whilst to induce a specific form and level of risk-aversion in agents, RPIP was implemented by setting:

$$G_i(q_i) = \frac{1582}{40}\sum_{t=1}^{40}(1 - e^{-0.005 q_{it}}) \tag{11}$$

In what follows, the practice of partitioning the set $q_i = \{q_{i1}, \ldots, q_{iT}\}$ into $S < T$ partitions for the purpose of implementing RPIP is referred to as stage 'bundling' in the present paper. Hence, Equations 9-11 all involve some degree of bundling: the $S = 25$ lotteries in Equation 9 each bundle together 2 consecutive consequences, and the single, $S = 1$, lottery represented in both Equations 10 and 11 bundles together all 40 consequences. In subsequent analysis, in common with typical experimental practice, it is assumed that for all stages the realized value of q_{it} is revealed to the subject at the end of stage t.[13] Table 1 gives an idea of the variation in experimental design and implementation of RPIP observed in the literature. All of the articles in Table 1 featured multiple-stage experiments, where a stage is defined not by separate decisions, but by separate awards of experimental currency. The relevance of the final columns, headed 'Stage Dependence' and 'Nash Equilibria' will be discussed in detail in Sections III and IV of the paper. For the moment we can note

[13] Revealing q_{it} to subject i after each stage has the advantage that it may facilitate the subject's learning of the experimental environment and increase the rate at which behaviour converges. Without loss of generality, we also assume the lottery for each stage is played and the associated money award paid immediately on completion of the stage. Some experiments delay the lottery and associated payment until the end of the experiment, but this difference does not affect our results. It can be shown that the incentives facing subjects in the EUT framework are exactly the same as when the lotteries take place immediately after each stage.

from the table that a) fourteen of the twenty-two studies reviewed involved subject interaction, which was beyond the scope of the analysis in Dobbs and Miller (2012), and b) six of the twenty-two studies employed some degree of bundling in RPIP implementation, and these are spread across single-subject and multi-subject studies.

Table 1. Observed variation in experimental design and RPIP implementation

	Subject Interaction	**Bundling**[a]	**Stage Dependence**[b]	**Nash Equilibria**[c]
1) Berg *et al*. (1986), Waller (1988), Baiman and Lewis (1989)	No	No	Independent	N/A
2) Prasnikar (1993), Selten *et al*. (1999), Harrison *et al*. (2013)	No	Yes	Independent	N/A
3) Sprinkle (2000), Dobbs and Miller (2006)	No	No	Dependent	N/A
4) Cox *et al*. (1985), Walker *et al*. (1990), Berg *et al*. (1992), Blume *et al*. (1998)	Yes	No	Independent	Unique
5) Roth and Malouf (1979), Roth and Murnighan (1982), Roth *et al*. (1988)	Yes	No	Independent	None
6) Cooper *et al*. (1989, 1990, 1992, 1993)	Yes	No	Independent	Multiple
7) Harrison (1989), Frederickson and Waller (2005)	Yes	Yes	Independent	Unique
8) Murnighan *et al*. (1988)[d]	Yes	Yes	Independent	None

[a]Bundling is said to be present whenever the number of lotteries conducted is less than the number of separate awards of experimental currency to an individual subject. This could be because awards are combined in some way, such as in Equations 9-11 above, or because the random lottery technique is used. In the table, the presence of bundling implies $S < T$, but not necessarily full bundling, $S = 1$.

[b]Dependence is present when the probability distribution governing experimental currency awards depends on previous realisations of experimental currency, or on actions taken in previous stages.

[c]Some of the unique Nash equilibria involve subgame perfect equilibria. The papers with no Nash equilibrium test bargaining theories with unstructured message spaces.

[d]In this paper, players bargained over probability points in a binary lottery, but there was also a third money outcome possible in the event of no bargaining agreement. Without further analysis, it is not clear therefore how RPIP 'works' in this paper.

The objective of RPIP in multiple subject multi-stage experiments

In order to establish the validity of RPIP, and the conditions on which its validity might depend, it is necessary to firstly specify what the objective of RPIP is. What class of 'induced preferences' do experimenters wish to induce? For the single-stage scenario evaluated in Berg *et al.* (1986), the objective of including RPIP in the experimental design is mathematically well-defined: it is to induce some pre-specified preference ordering, which we will denote by $v_i(q_i)$. The RPIP procedure amounts to setting $v_i(q_i) = G_i(q_i)$. Subjects then behave *as if* maximising the expected value of $G_i(q_i)$. In contrast, for our analysis of RPIP in multiple-subject multi-stage experiments such as (8), ascribing intentions to researchers must necessarily be speculative, for their objectives when including RPIP in designs with multiple consequences, $q_i = \{q_{i1}, \dots, q_{iT}\}$, have never been set out formally. Inductive analysis of how RPIP has *actually* been employed suggests that, for each stage of the experiment, researchers seek to induce a preference ordering for q_i that is *independent* of q_i realized in all other stages of the sequence; that is, in stage t, the objective is to induce a preference ordering $v_{it}(q_{it})$ that is independent of all $q_{is}, s \neq t$. Independent preference orderings allow considerable flexibility to an experimenter, not least because there is no requirement for induced preferences to be identical in every stage. But one restriction *is* required. It involves the structure of induced preferences for the full set of experimental consequences, q_i. It is well known that an additively-separable preference function is sufficient for independent preference orderings over each individual consequence, but Koopmans (1972) has demonstrated that an additively-separable preference function is also necessary.[14] Given this result, for a general framework it seems reasonable to restrict attention to the class of additively-separable induced preference functions over the full set of consequences, q_i; that is,

$$v_i(q_i) = \sum_{t=1}^{T} v_{it}(q_{it}) \tag{12}$$

[14] For two-stage problems, independent preference orderings implies only separability, which is weaker than additive separability.

In order to represent the intended induced preference function under uncertainty, we can use the expectations operator $E(.)$ to write:

$$E\big(v_i(q_i)\big) = \sum_{t=1}^{T} E(v_{it}(q_{it})) \tag{13}$$

To maximize Equation 13, a dynamic programming approach should be used with, at every stage j, the subject selecting the action a_{ij} that maximizes $\sum_{t=j}^{T} E_{ij}(v_{it}(q_{it}))$, where the subscript on the expectations operator indicates that conditional expectations are taken at stage j, as a function of previous actions and realisations of q_i.

Stage independence and RPIP without bundling ($S = T$)

With the above preparation, we are in a position to present our results. This subsection deals with the polar case of no bundling, $S = T$, the most frequently observed implementation of RPIP in Table 1, with $v_i(q_i) = \sum_{t=1}^{T} G_{it}(q_{it})$. It is shown that a necessary and sufficient condition for the validity of RPIP in the no-bundling case involves both a form of 'stage independence' highlighted in the single-subject analysis of Dobbs and Miller (2012), but also some restrictions on the conjectures of subjects about the strategic actions other subjects will take. As we shall see, these conditions can amount to a significant restriction for experiments involving interactions across stages and subjects.

In the no-bundling case, with T lotteries, there are T money awards of either $\overline{x}$ or $\underline{x}$. The rewards at different stages are distinguished using subscripts (writing $x_{i1}, x_{i2}, \dots, x_{iT}$) and also by reference to ordered T-tuples $(x_{i1}, x_{i2}, \dots, x_{iT})$ such as $(\overline{x}, \underline{x}, \dots, \overline{x})$.[15] To establish propositions applicable to all

[15] The two prize levels have been held constant across lotteries. This is solely for expositional convenience. It makes no difference, at least in theory, if the two prize levels vary across lotteries, as long as they are not within the control of subjects. See the papers by Roth and Malouf (1979), Roth and Murnighan (1982), Murnighan *et al*. (1988) and Roth *et al*. (1988), lines 5 and 8 in Table 1, for examples of prize levels varying across subjects.

subjects, it is assumed preferences over $(x_{i1}, x_{i2}, \dots, x_{iT})$ for subject i are described by an arbitrary *VNM* utility function $U_i(x_{i1}, x_{i2}, \dots, x_{iT})$. For this multiple-award case, the non-satiation assumption is strengthened by stipulating that, for all i, t, increasing x_{it} whilst holding constant $x_{is}, s \neq t$, results in increased utility. It then follows that, for example, $U_i(\overline{x}, \underline{x}) > U_i(\underline{x}, \underline{x})$ and $U_i(\underline{x}, \overline{x}) > U_i(\underline{x}, \underline{x})$.

Definition 1: Stage independence is defined as a condition in which the conditional density function in Equation 8 can be multiplicatively decomposed and written as:

$$f(q_i|a_i, a_{-i}) = f_{i1}(q_{i1}|a_{i1}, a_{-i1}) \times f_{i2}(q_{i2}|a_{i2}, a_{-i2}) \times \dots \times f_{iT}(q_{iT}|a_{iT}, a_{-iT}) \quad (14)$$

or equivalently

$$f_{it}\left(q_{it}\middle|a_{it}, a_{-it}, a_{i(t-1)}, a_{-i(t-1)}, q_{i(t-1)}, \dots, a_{i1}, a_{-i1}, q_{i1}\right) = f_{it}(q_{it}|a_{it}, a_{-it})$$

This is a stronger requirement than 'statistical independence'. Statistical independence would merely allow Equation 8 to be multiplicatively decomposed and written as:

$$f(q_i|a_i, a_{-i}) = f_{i1}(q_{i1}|a_{i1}, a_{-i1}) \times f_{i2}(q_{i2}|a_{i2}, a_{-i2}, a_{i1}, a_{-i1}) \times \dots \\ \times f_{iT}\left(q_{iT}\middle|a_{iT}, a_{-iT}, a_{i(T-1)}, a_{-i(T-1)}, \dots, a_{i1}, a_{-i1}\right)$$

One could conceive of experimental designs in which the conditional density for q_{it} depends on subject decisions in earlier stages, but not on realized outcomes of q prior to stage t. However, the relevant necessary and sufficient condition for RPIP validity when there is no bundling, Proposition 1 of this article, involves stage independence given by Equation 14. Referring to Table 1, twenty of the twenty-two studies featured experimental designs satisfying stage independence given by Definition 1.

The proof of the necessity part of Proposition 1, which follows, makes use of the following lemma.

Lemma 1: Given a differentiable *VNM* utility function $U_i(x, y)$, if for all $x > y$:

i) $U_i(x, y) = U_i(y, x)$

ii) $U_i(x, x) - U_i(x, y) = U_i(y, x) - U_i(y, y)$

then the utility function is additively separable, $U_i(x, y) = u_i(x) + u_i(y)$.

Proof: See Appendix.

Proposition 1: For an arbitrary multi-stage multi-subject experiment, in which stages are not bundled, if each subject maximizes expected *VNM* utility, then regardless of personal preferences over the set of money rewards, the subject will behave *as if* having preferences over q_i, $v_i(q_i) = \sum_{t=1}^{T} G_{it}(q_{it})$, pre-specified by the experimenter *if and only if* the experimental design exhibits stage independence *and* the subject's conjectures regarding the actions of other subjects are independent of the subject's previous realisations of q.

Proof: See Appendix.

RPIP with full bundling ($S = 1$)

The previous subsection dealt with the polar case of no bundling, $S = T$; in this subsection, the focus is on the opposite polar case of full bundling, $S = 1$. In this setting we show that RPIP is theoretically valid for all multiple-subject multi-stage experiments as long as multiple consequences are fully bundled into a single binary lottery. The result can be proved using the same assumptions as the single-subject single-task case presented in Section II.

Proposition 2: For an arbitrary T stage ($T \geq 2$) experiment, if each subject maximizes expected *VNM* utility, then regardless of personal preferences over the set of money rewards, as long as the experimental currency consequences at each stage are bundled into a single lottery, $S = 1$, then each subject will behave as if having preferences over q_i, $v_i(q_i) = G_i(q_i)$, pre-specified by the experimenter.

Proof: See Appendix.

The importance of the above result for full bundling, $S = 1$, is that it offers a 'failsafe' method for implementing RPIP when other bundling solutions, $S > 1$, do not work. Reference to Table 1 shows, however, that bundling was not employed in two of the studies examined, even though it was necessary for valid implementation of RPIP because the studies involved stage dependence (line 3 of Table 1).

Proposition 2 for the full bundling case and the necessary condition for the no bundling case in Proposition 1 also have relevance to intermediate cases of bundling, $1 < S < T$. This is because when there is any failure of the necessary condition in Proposition 1, it is inappropriate to implement RPIP by offering a lottery reward at each stage. In such circumstances, however, a valid RPIP design is indicated by Proposition 2; namely, a single lottery reward must be implemented after the final stage. By contrast, when the sufficient condition in Proposition 1 is satisfied by the experimental design, the bundling decision is irrelevant to the validity of RPIP, leaving researchers with some degree of freedom as to how RPIP is implemented. We defer discussion of the studies involving strategic interaction until the next section, where we examine design issues. However, we may note immediately that the bundling solution *was* employed in three non-interactive studies, when it was unnecessary for valid implementation of RPIP because the studies involved stage independence (line 2 of Table 1). Bundling may have been employed for other reasons, but these other reasons were usually not made explicit or discussed.

IV. Conclusions and Implications for the Design of Experiments

In this section we discuss experimental design issues relating to Propositions 1 and 2, and then conclude with a summary of the paper's findings. Where experiments feature stage interdependence, correct implementation of RPIP requires that a single lottery is undertaken at the end of each set of interdependent stages. This in turn has consequences for the distribution of prizes that a subject might receive. In particular, for an experiment in which all stages are interdependent, the subject will receive only one of two prizes. By contrast, where there is a greater degree of stage independence, a greater array of prize levels becomes possible without affecting the validity of RPIP. That is, the distribution of rewards is affected by bundling, even if the mean payoff is not. There are reasons to prefer the standard implementation of no bundling when the decision structure permits, because it increases the range of possible prizes a subject may receive. The issue here concerns perceptions of fairness or trust in the experimenter. For example, if there was just a single lottery and a low or high prize, a subject who received a low prize might well doubt whether the random process had been implemented fairly or appropriately. A sensible compromise in cases where the essence of the basic experiment is one of stage interdependence is to have a sequence of such experiments, each of which is independent of the others. For each of these experiments, the payoff arises from a single binary lottery, but having in addition an independent sequence then generates a multiplicity of such lotteries. This would retain RPIP validity whilst increasing the set of potential overall rewards paid to subjects. Of course, if the overall burden on the subject is not to prove too onerous, there has to be a trade off between the number of interdependent stages within an experiment and the number of independent experiments in the sequence faced by subjects.

The importance of the strategic interaction of multiple subjects lies in the fact that a subject's conjectures about how other subjects will act affect the validity of RPIP. This brings out a dimension not addressed in the single-subject context of Dobbs and Miller (2012). Since subject actions are response variables under observation by the experimenter, in a multiple-subject setting a subject's conjectures about how other subjects will act cannot be fully controlled. The precise degree of control necessary for RPIP to work is one of the new results provided in the present paper. We have shown in Proposition 1 that when there is no bundling, part of the necessary and sufficient condition for the validity of RPIP is that each subject's conjectures regarding the actions of others are independent of his previous realisations of q.

To see what is at issue here, take the case of stage independence as in Definition 1. In this setting, RPIP ensures that a subject in the final stage will behave as if maximising the expected value of $G_{iT}(q_{iT})$, the value of which depends on his conjecture about a_{-iT}. Denote that conjecture as $\hat{a}_{-iT}$. Since, however, subject i's conjecture is supplied by him rather than the experimenter, without further restrictions, stage independence alone is not sufficient to rule out the possibility of his conjecture depending on $q_{it}, t < T$. Nor is the further restriction of confining attention to Nash equilibrium behaviour sufficient, since if there are multiple Nash equilibria in the final stage, there is a logical possibility that q_{it} might have a role to play in subjects selecting one or another of these Nash equilibria. For an example of stage independence, yet optimal decision making depending on $q_{it}, t < T$, consider repeated play of a one-shot coordination game such as 'Battle of the Sexes', which has two Nash equilibria. This was the setting of Cooper *et al*. (1989, 1990, 1992, 1993).[16] Realized q_{it} could be introduced by subjects as a coordination device, allowing them to reach one or another Nash equilibrium in the final stage. This then leads to the expected value of $G_{iT}(q_{iT})$ depending on q_{it} because $\hat{a}_{-iT}$ depends on q_{it}. Cooper et al avoided this problem by having subjects play the Battle of the Sexes game against unidentified players, with random re-matching of players at every repetition of the game.[17] Thus it is not rational for subject i to conjecture that his 'partner' will condition his stage T action on q_{it}, because he knows that by experimental design this variable is private information to him. Bundling is not therefore required if the anonymous re-matching device is adopted.

[16] See Table 1, line 6, of the present paper.
[17] Though their purpose in adopting this procedure was not related to RPIP, it was to avoid reputation effects arising when the same two players knowingly play repeated games together.

It is worth considering how 'independent conjectures' could be built into the design if anonymous re-matching was undesirable, perhaps because reputation effects were of specific interest to the researcher. In this case, confining attention to environments where at each stage there is a unique Nash equilibrium and subjects play their Nash strategies, removes the possibility of optimal decision-making depending on $q_{it}, t < T$.[18] Given the generalized conditional distribution function with stage independence, $F_{iT}(q_{iT}|a_{iT}, a_{-iT})$, then by the definition of the assumed unique Nash equilibrium at stage T, involving optimal actions (a^*_{iT}, a^*_{-iT}), it must be that

$$\int_{q_{iT}\in Q_{iT}} G_{iT}(q_{iT})\, dF_{iT}(q_{iT}|a^*_{iT}(a^*_{-iT}), a^*_{-iT}) \geq \int_{q_{iT}\in Q_{iT}} G_{iT}(q_{iT})\, dF_{iT}(q_{iT}|a'_{iT}(a^*_{-iT}), a^*_{-iT}), \quad \forall i, \forall a'_{iT}$$

Since, at this Nash equilibrium, a^*_{-iT} is unique and there is a unique best response for subject *i*, it is by definition irrational for the conjectured actions of others to be anything but a constant. Hence a no-bundling implementation of RPIP will work as intended. The studies in line 4 and line 7 of Table 1 are stage independent and possess a unique Nash equilibrium at each stage. They are therefore consistent with valid RPIP and no bundling, though in Harrison (1989) and Fredrickson and Waller (2005) bundling was nevertheless chosen. Unfortunately, if a stage has no Nash equilibrium or multiple Nash equilibria, we know of no mechanism other than anonymous re-matching of players for rescuing the validity of RPIP with no bundling. Hence in these circumstances, full bundling would be the appropriate implementation. The studies in lines 5 and 8 of Table 1 involved two-player bargaining with an unstructured message space. Although in these designs, there was anonymity and re-matching, the fact that subjects could send 'cheap talk' messages again raises the theoretical possibility that a subject's conjectures could depend on the message he sends about his previous realisations of q. This possibility casts doubt on the effectiveness of RPIP for these studies.

[18] In fact, RPIP will be valid without a unique Nash equilibrium in the first stage, since at this stage there can be no dependence of conjectures on previous values of q.

In summary we find that independence between multiple decision-making stages of an experiment is necessary and sufficient for the most widely-used implementation of binary lotteries, involving a one-to-one correspondence of stages to lotteries, a design described here as ‘no bundling’. When multi-subject experiments are under consideration, the idea of independence is broader than in Dobbs and Miller (2012), encompassing a subject’s conjectures about the relationship between the actions of others and his own previous realized awards of experimental currency. With interdependence, as defined in Proposition 1, the affected stages must be bundled together into a single lottery. Thus it has been shown formally that the scope of RPIP extends to multi-stage multiple-subject experimental settings, *as long as either* the stages are functionally independent *or* rewards of experimental currency are bundled together into a single lottery.

Appendix

This Appendix gives proofs for Propositions 1 and 2, and Lemma 1.

Lemma 1: Given a differentiable *VNM* utility function $U_i(x, y)$, if for all $x > y$:

i) $U_i(x, y) = U_i(y, x)$

ii) $U_i(x, x) - U_i(x, y) = U_i(y, x) - U_i(y, y)$

then the utility function is additively separable, $U_i(x, y) = u_i(x) + u_i(y)$.

Proof: Conditions i) and ii) imply

$$U_i(x, y) = U_i(y, x) = \frac{1}{2}\{U_i(x, x) + U_i(y, y)\} \tag{A.1}$$

Applying (A.1) to $U_i(w, x) - U_i(w, y) - U_i(z, x) + U_i(z, y)$, where w, z are arbitrary values:

$$\begin{gathered} U_i(w, x) - U_i(w, y) - U_i(z, x) + U_i(z, y) \\ = \frac{1}{2}\{U_i(w, w) + U_i(x, x)\} - \frac{1}{2}\{U_i(w, w) + U_i(y, y)\} \\ - \frac{1}{2}\{U_i(z, z) + U_i(x, x)\} + \frac{1}{2}\{U_i(z, z) + U_i(y, y)\} = 0 \end{gathered} \tag{A.2}$$

(A.2) shows that $U_i(w, x) - U_i(w, y) = U_i(z, x) - U_i(z, y)$, so utility differences arising from receiving x rather than y in the second stage do not depend on the value received in the first stage. Since $U_i(w, x) - U_i(w, y)$ is invariant with respect to the value of w, then $\frac{\partial U_i(w,x)}{\partial w} - \frac{\partial U_i(w,y)}{\partial w} = 0$. But this implies $\frac{\partial U_i(w,x)}{\partial w} = \frac{\partial U_i(w,y)}{\partial w}$, so that the partial derivative with respect to w is invariant with respect to the value received in the second stage. Thus $\frac{\partial^2 U_i(w,x)}{\partial w \partial x} = 0$. Integrating:

$$\iint \frac{\partial^2 U_i(w,x)}{\partial w \partial x} dxdw = U_i(w,x) = h_i(w) + u_i(x)$$

where $h_i(w), u_i(x)$ are arbitrary functions. But from condition i)

$$U_i(w,x) = h_i(w) + u_i(x) = U_i(x,w) = h_i(x) + u_i(w)$$

Hence $h_i(x) = u_i(x)$. ■

The converse proposition, that additively-separable utility implies conditions i) and ii), is trivial.

For Proposition 1 below, it will be convenient to introduce some new definitions in order to reduce notational clutter. Let

$$\begin{aligned} U_i(\overline{x},\overline{x}) - U_i(\underline{x},\overline{x}) &\equiv u_i^1 \\ U_i(\overline{x},\overline{x}) - U_i(\overline{x},\underline{x}) &\equiv u_i^2 \\ U_i(\overline{x},\underline{x}) - U_i(\underline{x},\underline{x}) &\equiv u_i^3 \\ U_i(\underline{x},\overline{x}) - U_i(\underline{x},\underline{x}) &\equiv u_i^4 \end{aligned} \tag{A.3}$$

Note that, because utility is strictly increasing in pay-offs (non-satiation), $u_i^1, u_i^2, u_i^3, u_i^4 > 0$. A further useful identity is that $u_i^1 - u_i^3 \equiv u_i^2 - u_i^4$.

Proposition 1: For an arbitrary multi-stage multi-subject experiment, in which stages are not bundled, if each subject maximizes expected *VNM* utility, then regardless of personal preferences over the set of money rewards, the subject will behave *as if* having preferences over q_i, $v_i(q_i) = \sum_{t=1}^{T} G_{it}(q_{it})$, pre-specified by the experimenter *if and only if* the experimental design exhibits stage independence *and* the subject's conjectures regarding the actions of other subjects are independent of the subject's previous realisations of q.

Proof: For expositional convenience, we focus on a two-stage experiment.[19] We seek to examine the conditions under which, at stage two, an arbitrary subject *i* behaves as if he is maximising $E_{i2}\{G_{i2}(q_{i2})\}$ as a function of $(a_{i1}, \hat{a}_{-i1}, q_{i1})$, where $\hat{a}_{-i1}$denotes the subject's conjecture about a_{-i1}, and at stage one he acts as if he is maximising $E_{i1}\{G_{i1}(q_{i1})\} + E_{i1}\{G_{i2}(q_{i2})\}$ taking into account the interdependence between stages one and two.

At stage two, the subject knows q_{i1} and x_{i1}, the latter being either $\overline{x}$ or $\underline{x}$. For an arbitrary set of conjectures for the actions of all other subjects, $\hat{a}_{-i2}$, $\hat{a}_{-i1}$, and regardless of the value of x_{i1}, the subject's decision problem for choosing an action, a_{i2}, in order to maximize his expected *VNM* utility from the lottery is:

$$\max_{a_{i2}\in A_{i2}} \int_{q_{i2}\in Q_{i2}} \{G_{i2}(q_{i2})U_i(x_{i1},\overline{x}) + \left(1-G_{i2}(q_{i2})\right)U_i\left(x_{i1},\underline{x}\right)\} \, dF_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}) \tag{A.4}$$

where $F_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})$ is the distribution function corresponding to the generalized probability density function $f_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})$. Equation A.4 can be re-written as:

$$\max_{a_{i2}\in A_{i2}} \left(U_i\left(x_{i1},\underline{x}\right) + \left\{ \int_{q_{i2}\in Q_{i2}} \begin{matrix} \left[U_i(x_{i1},\overline{x}) - U_i\left(x_{i1},\underline{x}\right)\right] \times \\ G_{i2}(q_{i2}) \, dF_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}) \end{matrix} \right\} \right) \tag{A.5}$$

$$\Rightarrow \operatorname*{argmax}_{a_{i2}\in A_{i2}} \left(U_i\left(x_{i1},\underline{x}\right) + \left\{ \int_{q_{i2}\in Q_{i2}} \begin{matrix} \left[U_i(x_{i1},\overline{x}) - U_i\left(x_{i1},\underline{x}\right)\right] \times \\ G_{i2}(q_{i2}) \, dF_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}) \end{matrix} \right\} \right) \tag{A.6}$$

[19] Proof of sufficiency for a T-stage experiment is available from the authors.

$$= a_{i2}^{*}(\hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}) = \underset{a_{i2}\in A_{i2}}{\operatorname{argmax}}\left(\int_{q_{i2}\in Q_{i2}} G_{i2}(q_{i2})\, dF_{i2}(q_{i2}|a_{i2}, \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1})\right)$$

Notice the optimal solution for a_{i2} does not depend on the constant term, $U_i(x_{i1}, \underline{x})$, nor does it depend on the positive term $[U_i(x_{i1}, \overline{x}) - U_i(x_{i1}, \underline{x})]$, hence the subject behaves as if maximising $E_{i2}\{G_{i2}(q_{i2})\}$, a function of $(\hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1})$. Since this is true for arbitrary $\hat{a}_{-i2}$ and $\hat{a}_{-i1}$, and for an arbitrary subject, it is true for all subjects, whatever their conjectures. Borrowing terminology from oligopoly theory, essentially the experimenter has full control over every subject's 'reaction function'. To obtain a solution to this one-shot final-stage game, the experimenter would have to predict subjects' conjectures. This can be achieved using the Nash equilibrium criterion, giving a solution that may involve dominant strategies, pure strategies, mixed strategies or multiple equilibria.[20] Hence, as long as we confine attention to the final stage, or equivalently to a one-stage problem, the validity of RPIP is quite general. Note especially that even if there is no prediction about the solution to the game, and indeed in some contexts an experimenter might wish to study a situation in which there is no Nash equilibrium, risk preferences of subjects are nevertheless pre-specified by the experimenter via choice of $G_{i2}(q_{i2})$.

It turns out that the validity of RPIP at earlier stages will crucially depend on whether the optimal value of the integral on the right hand side of (A.6) is a function of q_{i1}. With stage interdependence, this value clearly depends on q_{i1}. Denote this integral by $e_{i2}^{*}(q_{i1})$, notation which will be used to prove necessity. With stage independence, the optimal value may or may not depend on q_{i1}.[21] We will write e_{i2}^{*} as a constant if the optimal value of the integral on the right hand side of (A.6) is independent of q_{i1}, notation which will be used in the proof of sufficiency. Finally, note that since $G_{i2}(q_{i2})$ is a probability, it lies between 0 and 1, and so both $e_{i2}^{*}(q_{i1})$ and e_{i2}^{*}, the expected probabilities from optimal stage two decisions, also lie between 0 and 1.

[20] Although the existence of multiple equilibria does not prejudice the validity of RPIP in the final stage, as we shall see it could lead to problems in earlier stages.

[21] We discuss this point more fully in Section IV of the main text.

Proof of necessity

We proceed by proving the contrapositive of Proposition 1: namely, that if stages are interdependent, so we have $e_{i2}^*(q_{i1})$, then RPIP cannot work for *arbitrary* personal preferences over the set of money rewards.

At stage one, the subject's decision problem for maximising expected *VNM* utility, given optimal decision-making at stage two, can be written as:

$$\max_{a_{i1}\in A_{i1}}\left(\int_{q_{i1}\in Q_{i1}}\left(\int_{q_{i2}\in Q_{i2}}\left\{\begin{array}{c}\left[\begin{array}{c}G_{i1}(q_{i1})G_{i2}(q_{i2})U_i(\overline{x},\overline{x})\\+G_{i1}(q_{i1})\big(1-G_{i2}(q_{i2})\big)U_i(\overline{x},\underline{x})\\+(1-G_{i1}(q_{i1}))G_{i2}(q_{i2})U_i\big(\underline{x},\overline{x}\big)\\+(1-G_{i1}(q_{i1}))(1-G_{i2}(q_{i2}))U_i\big(\underline{x},\underline{x}\big)\end{array}\right]\\\times\, dF_{i2}(q_{i2}|a_{i2}^*(\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}),\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})\end{array}\right\}\right)dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right) \tag{A.7}$$

The central expression in square brackets in (A.7) can be simplified by the notation in (A.3), to give a restatement of (A.7) as:

$$\max_{a_{i1}\in A_{i1}}\left(\int_{q_{i1}\in Q_{i1}}\left(\int_{q_{i2}\in Q_{i2}}\left\{\begin{array}{c}\left[\begin{array}{c}G_{i1}(q_{i1})\{u_i^3+G_{i2}(q_{i2})\big(u_i^2-u_i^4\big)\}\\+G_{i2}(q_{i2})u_i^4+U_i\big(\underline{x},\underline{x}\big)\end{array}\right]\\\times\, dF_{i2}(q_{i2}|a_{i2}^*(\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}),\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})\end{array}\right\}\right)dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right) \tag{A.8}$$

Integrating with respect to $F_{i2}(q_{i2}|a_{i2}^*(\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}),\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})$, utilising the definition of $e_{i2}^*(q_{i1})$, then gives:

$$\max_{a_{i1}\in A_{i1}}\left(\int_{q_{i1}\in Q_{i1}}\left[\begin{array}{c}U_i\big(\underline{x},\underline{x}\big)+u_i^3G_{i1}(q_{i1})+\\\{u_i^4+(u_i^2-u_i^4)G_{i1}(q_{i1})\}e_{i2}^*(q_{i1})\end{array}\right]dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right) \tag{A.9}$$

Given the objective of RPIP at stage one, namely to maximize $E_{i1}\{G_{i1}(q_{i1})\}+E_{i1}\{G_{i2}(q_{i2})\}$, the procedure will be effective in reducing (A.9) to this objective function if and only if:

$$\underset{a_{i1}\in A_{i1}}{\operatorname{argmax}}\left(\int\limits_{q_{i1}\in Q_{i1}}\begin{bmatrix} U_i(\underline{x},\underline{x}) + u_i^3 G_{i1}(q_{i1}) + \\ \{u_i^4 + (u_i^2 - u_i^4)G_{i1}(q_{i1})\}e_{i2}^*(q_{i1}) \end{bmatrix} dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right)$$

$$= \underset{a_{i1}\in A_{i1}}{\operatorname{argmax}}\left(\int\limits_{q_{i1}\in Q_{i1}} [G_{i1}(q_{i1}) + e_{i2}^*(q_{i1})] dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1}))\right) \tag{A.10}$$

If stage independence is not assumed, then Equation A.10 can be true for *arbitrary* subject preferences if and only if:

$$\begin{bmatrix} U_i(\underline{x},\underline{x}) + u_i^3 G_{i1}(q_{i1}) + \\ \{u_i^4 + (u_i^2 - u_i^4)G_{i1}(q_{i1})\}e_{i2}^*(q_{i1}) \end{bmatrix} = \alpha_i + \beta_i[G_{i1}(q_{i1}) + e_{i2}^*(q_{i1})] \tag{A.11}$$

where α_i, β_i are constants and $\beta_i > 0$. To prove the necessity of stage independence, it suffices to prove that A.11, which assumes the opposite mutually exclusive condition of stage interdependence, leads to a contradiction.

Equation A.11 is true if and only if $u_i^3 = u_i^4$ and $u_i^2 = u_i^4$.[22] From the definitions in (A.3) these two conditions necessarily imply, respectively, $U_i(\overline{x},\underline{x}) = U_i(\underline{x},\overline{x})$ and $U_i(\overline{x},\overline{x}) - U_i(\overline{x},\underline{x}) = U_i(\underline{x},\overline{x}) - U_i(\underline{x},\underline{x})$. Application of Lemma 1 then means that A.11 implies the subject's *VNM* utility function is additively separable in (x_1, x_2). That is, if stages are interdependent, RPIP is only valid if the subject's *VNM* utility function is restricted to be additively separable. This contradicts Proposition 1, which requires that RPIP should hold for *arbitrary* preferences over money consequences.

<u>Proof of sufficiency</u>

To prove sufficiency, assume e_{i2}^* is a constant, independent of q_{i1}. The maximand on the left hand side of A.10 becomes:

[22] Setting $\beta_i = u_i^3 = u_i^4$ also satisfies the condition $\beta_i > 0$.

$$\left\{U_i\left(\underline{x},\underline{x}\right)+u_i^4 e_{i2}^*\right\}+\left\{u_i^3+\left(u_i^2-u_i^4\right)e_{i2}^*\right\}\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1}) \tag{A.12}$$

$$\begin{aligned}\Rightarrow \underset{a_{i1}\in A_{i1}}{argmax}&\left(\left\{U_i\left(\underline{x},\underline{x}\right)+u_i^4 e_{i2}^*\right\}+\left\{u_i^3+\left(u_i^2-u_i^4\right)e_{i2}^*\right\}\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right)\\ &=\underset{a_{i1}\in A_{i1}}{\operatorname{argmax}}\left(\left\{u_i^3+\left(u_i^2-u_i^4\right)e_{i2}^*\right\}\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right)\end{aligned} \tag{A.13}$$

and the maximand on the right hand side of A.10 becomes:

$$e_{i2}^*+\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}\left(q_{i1}\middle|a_{i1},\hat{a}_{-i1}\right) \tag{A.14}$$

$$\begin{aligned}\Rightarrow \underset{a_{i1}\in A_{i1}}{\operatorname{argmax}}&\left(e_{i2}^*+\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}\left(q_{i1}\middle|a_{i1},\hat{a}_{-i1}\right)\right)\\ &=\underset{a_{i1}\in A_{i1}}{\operatorname{argmax}}\left(\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}\left(q_{i1}\middle|a_{i1},\hat{a}_{-i1}\right)\right)\end{aligned} \tag{A.15}$$

Equating the right hand sides of A.13 and A.15:

$$\begin{aligned}\underset{a_{i1}\in A_{i1}}{\operatorname{argmax}}&\left(\left\{u_i^3+\left(u_i^2-u_i^4\right)e_{i2}^*\right\}\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right)\\ &=\underset{a_{i1}\in A_{i1}}{\operatorname{argmax}}\left(\int_{q_{i1}\in Q_{i1}} G_{i1}(q_{i1})dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1})\right)\end{aligned} \tag{A.16}$$

Equation A.16 will be true if and only if $u_i^3+\left(u_i^2-u_i^4\right)e_{i2}^*>0$. Given the identity $u_i^1-u_i^3\equiv u_i^2-u_i^4$, the condition can also be written as:

$$u_i^3 + (u_i^2 - u_i^4)e_{i2}^* = u_i^3 + e_{i2}^*(u_i^1 - u_i^3) = e_{i2}^* u_i^1 + (1 - e_{i2}^*)u_i^3 > 0 \tag{A.17}$$

Finally, since $u_i^1, u_i^3 > 0$ by (A.3) and $e_{i2}^*, (1 - e_{i2}^*) > 0$, A.17 is satisfied. ■

Proposition 2: For an arbitrary T stage ($T \geq 2$) experiment, if each subject maximizes expected *VNM* utility, then regardless of personal preferences over the set of money rewards, as long as the experimental currency consequences at each stage are bundled into a single lottery, $S = 1$, then each subject will behave as if having preferences over q_i, $v_i(q_i) = G_i(q_i)$, pre-specified by the experimenter.

Proof: The objective is to prove that at stage two, each subject behaves as if maximising $E_{i2}(v_{i2}(q_{i2}))$ as a function of $(q_{i1}, a_{i1}, \hat{a}_{-i1})$, and at stage one he acts as if maximising $E_{i1}(v_{i1}(q_{1i})) + E_{i2}(v_{i2}(q_{i2}))$ taking into account the interdependence between stages one and two. First consider the decision problem in the second and final stage, where the subject must choose an action, a_{i2}, in order to maximize expected *VNM* utility from the lottery. For an arbitrary set of conjectures for the actions of all other subjects, $\hat{a}_{-i2}$, $\hat{a}_{-i1}$, the subject's decision problem is:

$$\max_{a_{i2} \in A_{i2}} \left(\int_{q_{i2} \in Q_{i2}} \{G_i(q_i)U_i(\overline{x}) + \left(1 - G_i(q_i)\right)U_i\left(\underline{x}\right)\} \, dF_{i2}(q_{i2} | a_{i2}, \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}) \right) \tag{A.18}$$

where $F_{i2}(q_{i2} | a_{i2}, \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1})$ is the generalized distribution function corresponding to the generalized probability density function $f_{i2}(q_{i2} | a_{i2}, \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1})$ for arbitrary conjectures $\hat{a}_{-i2}, \hat{a}_{-i1}$.

Equation A.18 can be subjected to rearrangements that exactly mirror Equations 3 to 6 in the main text of the paper, leaving:

$$\max_{a_{i2}\in A_{i2}}\left(U_i(\underline{x})+[U_i(\overline{x})-U_i(\underline{x})]\int_{q_{i2}\in Q_{i2}} G_i(q_i)\,dF_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})\right) \tag{A.19}$$

Since the single lottery satisfies Equation 12, $G_i(q_i)=v_i(q_i)=v_{i1}(q_{i1})+v_{i2}(q_{i2})$, and A.19 can be further reduced to:

$$\max_{a_{i2}\in A_{i2}}\left(\begin{array}{c} U_i(\underline{x})+[U_i(\overline{x})-U_i(\underline{x})]v_{i1}(q_{i1})+ \\ [U_i(\overline{x})-U_i(\underline{x})]\int_{q_{i2}\in Q_{i2}} v_{i2}(q_{i2})\,dF_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}) \end{array}\right) \tag{A.20}$$

so that, given $U_i(\overline{x})>U_i(\underline{x})$, the optimal decision at stage two, $a_{i2}^*(\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})$ is

$$a_{i2}^*(\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})=\underset{a_{i2}\in A_{i2}}{\operatorname{argmax}}\left(\int_{q_{i2}\in Q_{i2}} v_{i2}(q_{i2})\,dF_{i2}(q_{i2}|a_{i2},\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})\right) \tag{A.21}$$

Thus regardless of the subject's conjectures, and the realized outcome, q_{i1}, from the previous decision, a_{i1}, the subject behaves as if maximising $E_{i2}(v_{i2}(q_{i2}))$ in accordance with the preference ordering pre-specified in the experimental design.

Turning to stage one, the subject's decision problem is to choose an action, a_{i1}, taking account of optimal decision-making going forward: $a_{i2}^*(\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})$. Thus at stage one, the subject aims to maximize:

$$\int_{q_{i1}\in Q_{i1}}\left(\int_{q_{i2}\in Q_{i2}}\begin{array}{c}\{G_i(q_i)U_i(\overline{x})+(1-G_i(q_i))U_i(\underline{x})\} \\ \times\, dF_{i2}(q_{i2}|a_{i2}^*(\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1}),\hat{a}_{-i2},a_{i1},\hat{a}_{-i1},q_{i1})\end{array}\right)dF_{i1}(q_{i1}|a_{i1},\hat{a}_{-i1}) \tag{A.22}$$

Equation A.22 can again be simplified to give:

$$U_i(\underline{x}) + [U_i(\overline{x}) - U_i(\underline{x})] \times$$

$$\left(\int_{q_{i1} \in Q_{i1}} \int_{q_{i2} \in Q_{i2}} G_i(q_i) dF_{i2}(q_{i2} | a_{i2}^*(\hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}), \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1})\, dF_{i1}(q_{i1} | a_{i1}, \hat{a}_{-i1}) \right) \tag{A.23}$$

so that, given $U_i(\overline{x}) > U_i(\underline{x})$, the optimal decision at stage one is:

$$\underset{a_1 \in A_1}{\text{argmax}} \left(\int_{q_{i1} \in Q_{i1}} \int_{q_{i2} \in Q_{i2}} G_i(q_i) dF_{i2}(q_{i2} | a_{i2}^*(\hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}), \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1})\, dF_{i1}(q_{i1} | a_{i1}, \hat{a}_{-i1}) \right) \tag{A.24}$$

Substituting $G_i(q_i) = v_i(q_i) = v_{i1}(q_{i1}) + v_{i2}(q_{i2})$, into A.24, then rearranging gives:

$$\underset{a_1 \in A_1}{\text{argmax}} \left(\int_{q_{i1} \in Q_{i1}} \left(\int_{q_{i2} \in Q_{i2}} \begin{Bmatrix} (v_{i1}(q_{i1}) + v_{i2}(q_{i2})) \\ \times\, dF_{i2}(q_{i2} | a_{i2}^*(\hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}), \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}) \end{Bmatrix} \right) dF_{i1}(q_{i1} | a_{i1}, \hat{a}_{-i1}) \right) \tag{A.25}$$

$$\Rightarrow \underset{a_1 \in A_1}{\text{argmax}} \left(\int_{q_{i1} \in Q_{i1}} \left(\begin{matrix} v_{i1}(q_{i1}) + \int_{q_{i2} \in Q_{i2}} \begin{Bmatrix} v_{i2}(q_{i2}) \\ \times\, dF_{i2}(q_{i2} | a_{i2}^*(\hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}), \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}) \end{Bmatrix} \\ \times\, dF_{i1}(q_{i1} | a_{i1}, \hat{a}_{-i1}) \end{matrix} \right) \right) \tag{A.26}$$

$$\Rightarrow \underset{a_1 \in A_1}{\text{argmax}} \left(\begin{matrix} \int_{q_{i1} \in Q_{i1}} v_{i1}(q_{i1}) dF_{i1}(q_{i1} | a_{i1}, \hat{a}_{-i1}) + \\ \int_{q_{i1} \in Q_{i1}} \int_{q_{i2} \in Q_{i2}} v_{i2}(q_{i2}) dF_{i2}(q_{i2} | a_{i2}^*(\hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}), \hat{a}_{-i2}, a_{i1}, \hat{a}_{-i1}, q_{i1}) dF_{i1}(q_{i1} | a_{i1}, \hat{a}_{-i1}) \end{matrix} \right) \tag{A.27}$$

However, Equation A.26 is precisely the definition of the optimal action for maximising $E_{i1}(v_{i1}(q_{1i})) + E_{i2}(v_{i2}(q_{i2}))$ at stage one. Since this is true for arbitrary $\hat{a}_{-i2}$ and $\hat{a}_{-i1}$, and for an arbitrary subject, it is true for all subjects, whatever their conjectures. As long as we confine attention to RPIP with full bundling, the validity of RPIP is quite general. ■

References

Baiman, S. and Lewis, B. L. (1989) An Experiment Testing the Behavioral Equivalence of Strategically Equivalent Employment Contracts, *Journal of Accounting Research*, **27**, 1-20.

Berg, J. E., Daley, L. A., Dickhaut, J. W. and O'Brien, J. R. (1986) Controlling Preferences for Lotteries on Units of Experimental Exchange, *Quarterly Journal of Economics*, **101**, 281-306.

Berg, J. E., Daley, L. A., Dickhaut, J. W. and O'Brien, J. (1992) Moral Hazard and Risk Sharing: Experimental Evidence, in *Research in Experimental Economics*, Volume 5, (Ed) R. M. Isaac, JAI Press, Greenwich, Connecticut, 1-34.

Berg, J. E., Dickhaut, J. W. and Rietz, T. A. (2003) Preference Reversals and Induced Risk Preferences: Evidence for Noisy Maximisation, *Journal of Risk and Uncertainty,* **27**, 139-170.

Berg, J. E., Dickhaut, J. W. and Rietz, T. A. (2008) On the Performance of the Lottery Procedure for Controlling Risk Preferences, in *The Handbook of Experimental Economics Results,* Volume 1, (Eds) C. R. Plott and V. L. Smith, North Holland, Amsterdam.

Billingsley, P. (1995). Probability and Measure, 3rd edn, Wiley, New York.

Blume, A., DeJong, D. V., Kim, Y-G. and Sprinkle, G. B. (1998) Experimental Evidence on the Evolution of Meaning of Messages in Sender-Receiver Games, *The American Economic Review*, **88**, 1323-1340.

Cooper, R., DeJong, D.V., Forsythe, R. and Ross, T. W. (1989) Communication in the Battle of Sexes Game: Some Experimental Results, *RAND Journal of Economics*, **20**, 568-587.

Cooper, R., DeJong, D. V., Forsythe, R. and Ross, T. W. (1990) Selection Criteria in Coordination Games: Some Experimental Results, *American Economic Review*, **80**, 218-233.

Cooper, R, DeJong, D. V., Forsythe, R. and Ross, T. W. (1992) Communication in Coordination Games, *Quarterly Journal of Economics*, **107**, 1992, 739-771.

Cooper, R., DeJong, D. V., Forsythe, R. and Ross, T. W. (1993) Forward Induction in the Battle-of-the-Sexes Game, *American Economic Review*, **83**, 1303-1316.

Cox, J. C. and Oaxaca, R. L. (1995) Inducing Risk-Neutral Preferences: Further Analysis of the Data, *The Journal of Risk and Uncertainty*, **11**, 65-79.

Cox, J. C., Smith, V. L. and Walker, J. M. (1985) Experimental Development of Sealed-Bid Auction Theory; Calibrating Controls for Risk Aversion, *American Economic Review*, **75**, 160-165.

Cox, J. C., Smith, V. L. and Walker, J. M. (1988) Theory and Individual Behavior of First-Price Auction, *The Journal of Risk and Uncertainty*, **1**, 61-99.

Dobbs, I. M. and Miller, A. D. (2006) *The Impact of Financial Incentives on Decision-Making*, The Institute of Chartered Accountants of Scotland, Edinburgh.

Dobbs, I. M. and Miller, A. D. (2008) *The Impact of Financial Incentives on Decision-Making: Further Evidence*, The Institute of Chartered Accountants of Scotland, Edinburgh.

Dobbs, I. M. and Miller, A. D. (2009) Experimental Evidence on Financial Incentives, Information and Decision-Making, *British Accounting Review*, **41**, 71-89.

Dobbs, I. M. and Miller, A. D. (2012) Inducing Risk Preferences in Economic Experiments, *Applied Economics Letters*, **19**, 657-660.

Fisher, J. G., Maines, L. A., Peffer, S. A. and Sprinkle, G. B. (2002) Using Budgets for Performance Evaluation: Effects of Resource Allocation and Horizontal Information Asymmetry on Budget Proposals, Budget Slack, and Performance, *Accounting Review*, **77**, 847-865.

Fisher, J. G., Peffer, S. A. and Sprinkle, G. B. (2003) Budget-Based Contracts, Budget Levels and Group Performance, *Journal of Management Accounting Research*, **15**, 51-74.

Frederickson, J. R. and Waller, W. S. (2005) Carrot or Stick? Contract Frame and Use of Decision-Influencing Information in a Principal-Agent Setting, *Journal of Accounting Research*, **43**, 709-733.

Gonzalez, R. and Wu, G. (1999) On the Shape of the Probability Weighting Function, *Cognitive Psychology*, **38**, 129-166.

Harrison, G. W. (1989) Theory and Misbehavior of First-Price Auctions, *American Economic Review*, **79**, 749-762.

Harrison, G. W., Martinez-Correa, J. and Swarthout, J. T. (2013) Inducing Risk Neutral Preferences with Binary Lotteries: A Reconsideration, *Journal of Economic Behavior & Organization*, **94**, 145-159.

Harrison, G. W. and McCabe, K. A. (1992) Testing Noncooperative Bargaining Theory in Experiments, in *Research in Experimental Economics*, Volume 5, (Ed) R. M. Isaac, JAI Press, Greenwich, Connecticut, 137-169.

Isaac, R. M., Walker, J. M. and Williams, A. W. (1994) Group Size and the Voluntary Provision of Public Goods: Experimental Evidence Utilizing Large Groups, *Journal of Public Economics*, **54**, 1-36.

Koopmans, T. C. (1972) Representation of Preference Orderings with Independent Components of Consumption, in *Decision and Organization: A Volume in Honor of Jacob Marschak*, (Eds) C. B. McGuire and R. Radner, North-Holland Publishing Co, Amsterdam.

Laffont, J. and Martimort, D. (2002) *The Theory of Incentives: The Principal-Agent Model*, Princeton University Press, Princeton.

Murnighan, J. K., Roth, A. E. and Schoumaker, F. (1989) Risk Aversion in Bargaining: An Experimental Study, *Journal of Risk and Uncertainty*, **1**, 101-124.

Prasnikar, V. (1993) Binary Lottery Payoffs: Do They Control Risk Aversion? Discussion Paper 1059, Center for Mathematical Studies in Economics and Management Sciences, Northwestern University, Evaston, Illinois.

Rietz, T. A. (1993) Implementing and Testing Risk Preference Induction Mechanisms in Experimental Sealed Bid Auctions, *The Journal of Risk and Uncertainty*, **7**, 199-213.

Roth, A. E. and Malouf, M. W. K. (1979) Game-Theoretic Models and the Role of Information in Bargaining, *Psychological Review*, **86**, 574-594.

Roth, A. E. and Murnighan, J. K. (1982) The Role of Information in Bargaining: An Experimental Study, *Econometrica*, **50**, 1123-1142.

Roth, A. E., Murnighan, J. K. and Schoumaker, F. (1988) The Deadline Effect in Bargaining: Some Experimental Evidence, *The American Economic Review*, **78**, 806-823.

Selten, R., Sadrieh, A. and Abbink, K. (1999) Money Does Not Induce Risk Neutral Behavior, But Binary Lotteries Do Even Worse, *Theory and Decision*, **46**, 211-249.

Sprinkle, G. B. (2000) The Effect of Incentive Contracts on Learning and Performance, *Accounting Review*, **75**, 299-326.

Walker, J. M., Smith, V. L. and Cox, J. C. (1990) Inducing Risk-Neutral Preferences: An Examination in a Controlled Market Environment, The Journal of Risk and Uncertainty, **3**, 5-24.

Waller, W. (1988) Slack in Participative Budgeting: The Joint Effect of a Truth-Inducing Pay Scheme and Risk Preferences, *Accounting, Organizations and Society*, **13**, 87-98.